ACVM - 1. Assignment - Optical Flow

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I. Introduction

In this assignment we explore 2 basic optical flow methods: Lucas-Kanade and Horn-Schunck. We study their operations, limitations and potential improvements.

II. Experiments

A. Base implementation

We start off with a base implementation of each of the methods. We first test them in a controlled setting with a noise image which was rotated by 1 degree, shown in figure 1. The used implementations are basic, with the exception of better spatial and temporal derivatives discussed during class.

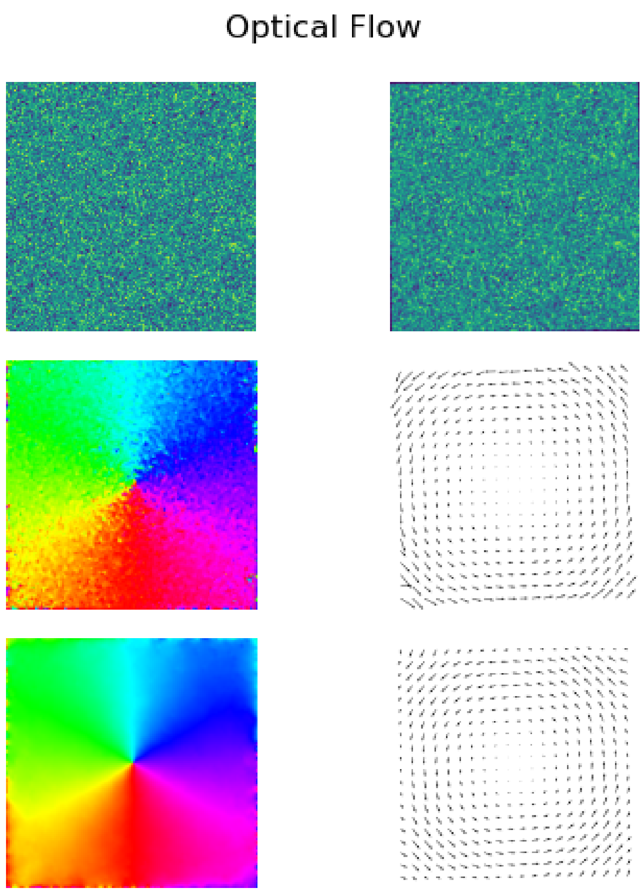

Figure 1. Visualization of the resulting optical flow of the Lucas-Kanade method (middle) and Horn-Schunck method (bottom)

Figures 2 and 3 show results of Lukas-Kanade and Horn-Schunck methods on actual images.

B. Time measurement

Time measurement of each method is shown in table II-B. Time was measured on a sequence of noise images and a sequence of toy car images. The improved Horn-Schunck method which is initialized with the output of Lucas-Kanade method

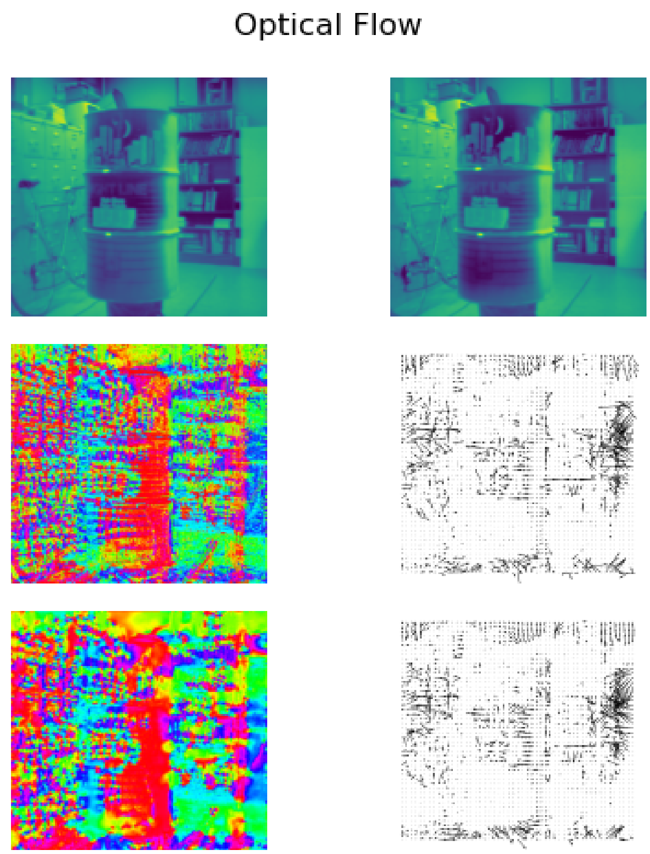

Figure 2. Visualization of the resulting optical flow of the Lucas-Kanade method (middle) and Horn-Schunck method (bottom)

seems to be slightly slower. We can also notice how the time needed is increased for more complex images, Lucas-Kanade slightly slows down, while Horn-Schunck becomes incredibly slow.

This implementation of Horn-Schunck doesn't have a fixed amount of iterations, the algorithm stops once it converges (when the largest update in the optical flow would be 0.01).

	Lucas-Kanade	Horn-Schunck	Improved HS	Image
Time	∼0.04 s	∼0.15 s	∼0.2 s	Noise
Time	∼0.07 s	∼4.5 s	∼4.5 s	Car

Table I
Time measurements for each method.

C. Parameters

The parameter we can set for Lucas-Kanade is the kernel size or rather the neighbourhood of pixels which we expect to move in the same direction. E.g. if we increase the kernel size beyond the size of the moving object, the estimated motion will be off or rather the resulting warped image will be messy/blurred (shown in figure 4).

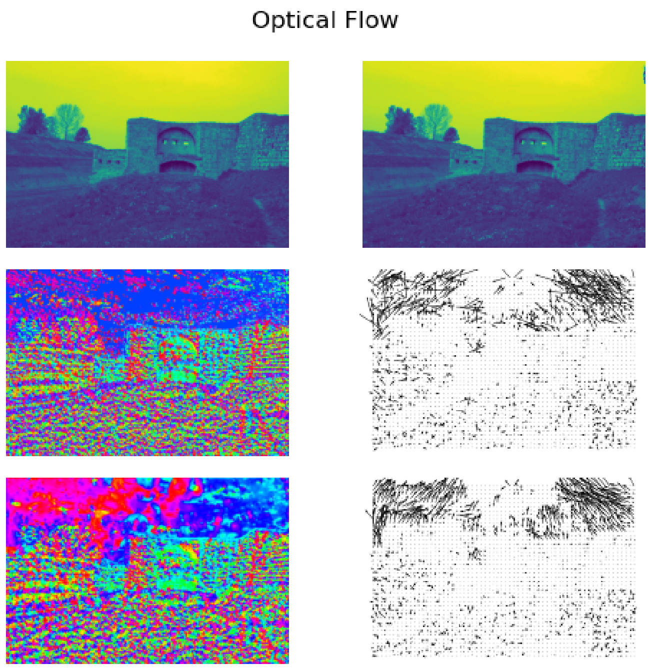

Figure 3. Visualization of the resulting optical flow of the Lucas-Kanade method (middle) and Horn-Schunck method (bottom)

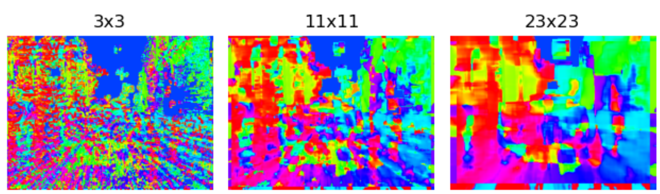

Figure 4. Comparing results of Lucas-Kanade with different kernel sizes.

The parameter we can set for Horn-Schunck is lambda, which is a regularization parameter that controls the trade-off between the data fidelity and the smoothness regularization. I couldn't find a proper example to showcase this, I tried the general values (0.5, 1, 2, 5) and it seemed all the same to me.

D. Limitations and improvements

1) Harris response: Next let's delve in to the limitations of the Lucas-Kanade method.

Because of the brightness consistency assumption, the optical flow gets chaotic in image regions with consistent colors or low textures. We can improve this by masking out regions determined to be unreliable. We evaluate reliability with the Harris response with a threshold of 0.04 (we want to keep corners/edges, but mostly corners).

As seen in figure 5, the chaotic optical flow on the walls, floor and the furniture in the back, which has consistent colors has been removed.

2) Guassian pyramid: The other assumption is regarding small displacements between sequenced images. To remedy this, we can use the Gaussian pyramid, which uses a coarse-to-fine approach by iteratively refining the motion estimates in each layer.

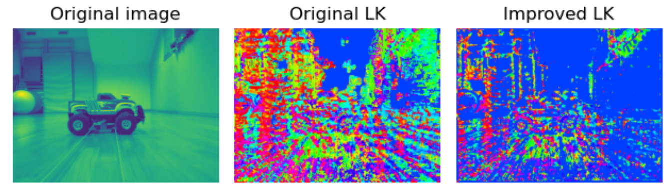

Figure 5. Visualization of the improvement with Harris response masking.

The used implementation uses 4 layers with 5 iterations in each of them, where we add the residual flow left over after warping. More iterations in each layer improves the result, but only to a certain degree (e.g. clear difference going from 1 to 2 to 3 iterations, small improvement from 4 to 5 and no clear improvement after 5 iterations).

Figure 6 shows a noise image which is rotated 5 degrees and visualizes how the pyramid implementation improves the movement estimates for large displacements (outer edges).

Regarding the artifacts on the edges, I'm not sure whether there's something wrong with how I added the results of each pyramid layer or it's something that happens because of up-sampling and interpolation.

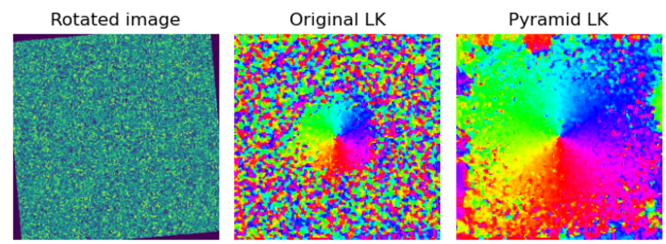

Figure 6. Visualization of the improvement with iterative Gaussian pyramid

III. Conclusion

Overall, this assignment provided valuable insights into the operation, strengths, and weaknesses of Lucas-Kanade and Horn-Schunck optical flow methods. While both methods have their advantages and limitations, understanding their behavior and leveraging appropriate techniques can lead to more accurate and robust motion estimation in various applications, from video analysis to robotics and computer vision.